SYSTEM IDENTIFICATION OF HEAT EXCHANGER USING GENERALIZED POISSON MOMENT FUNCTIONAL (GPMF)

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ABSTRACT

This project present a system identification of heat exchanger using Generalized Poisson Moment Functional (GPMF) method based on Instrumental Variable (IV) algorithm and Least Square. The purpose of this project is to develop a mathematical model from input-output data that properly represents the heat exchanger QAD BDT 921 system characteristics.The MATLAB coding consists of data pre-processing, parameter estimation, model validation and model simulation. A validation process had been implemented. Simulation process based on the estimated mathematical model was performed to analyze the dynamic behaviours of the model. The comparison between IV and Least Square Estimator is performed to compare the accurate estimation. From the simulation results and analysis, it could be concluded that the model obtained is reliable.

ABSTRAK

Projek ini membentangkan pengenalan sistem penukar haba menggunakan kaedah Generalized Poisson Moment Fungsian (GPMF) berdasarkan Instrumental Variable (IV) algoritma dan Least Square. Tujuan projek ini adalah untuk membangunkan satu model matematik daripada data input-output yang betul mewakili ciri-ciri sistem penukar haba QAD BDT 921. Pengekodan MATLAB yang mengandungi data pra-pemprosesan, anggaran parameter, pengesahan model dan simulasi model. Proses pengesahan telah dilaksanakan. Proses simulasi yang berdasarkan kepada anggaran model matematik telah dilaksanakan untuk menganalisis ciri dinamik model. Perbandingan antara IV dan Least Square Estimator dilakukan untuk membandingkan anggaran yang tepat. Dari keputusan simulasi dan analisis, ia boleh disimpulkan bahawa model yang diperoleh boleh dipercayai.

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LIST OF SYMBOLS AND ABBREVIATIONS

GPMF   -   Generalized Poisson Moment Functional

PMF   -   Poisson Moment Functional

CT   -   Continuous Time

DT   -   Discrete Time

SISO   -   Single Input Single Output

MIMO   -   Multiple Input Multiple Output

LS   -   Least Square

FPE   -   Final Prediction Error

PID   -   Proportional Integral Differential

CONTSID   -   Continuous Time System Identification

UTHM   -   Universiti Tun Hussein Onn Malaysia

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CHAPTER 1

INTRODUCTION

1.1 Project Background

The aim of this project is to identify a mathematical model of a heat exchanger called QAD Model BDT921, which uses shell and tube heat type. The Heat Exchanger QAD Model BDT921 is located at Faculty of Electric and Electronic Engineering in Universiti Tun Hussein Onn Malaysia.

This project is mainly concerned to find the mathematical model for the Heat Exchanger QAD Model BDT921. System identification method is used to identify the model of this system. Therefore it is necessary to collect the input and output data of the Heat Exchanger QAD Model BDT921. The estimation algorithm used in this project is Poisson Moment Functional (PMF). The input and output data from the system will be compared with the simulated data resulting from the estimation algorithm.

The experiment is designed to check the reliability and accuracy of the existing equipment as well as to collect the real input-output data used for identification and model validation. The resulting model is then analysed.

1.2 Problem Statement

Nowadays, much of the current literature on identification is concerned with the identification of continuous-time models. Furthermore, for many applications, continuous time models are more appealing to engineers than discrete-time models because they are closely related to the underlying physical systems, whereas discrete-time model is considered to be defined at a sequence of time-instants related to measurement [21]. Of the existing continuous-time parameter estimation approaches based on an equation error approach which use transfer function models, the Poisson Moment Functional approach is claimed to be one of the best under noisy conditions.

1.3 Objectives

There are a few objectives that need to be achieved at the end of this project, which are:

1. To find the parameter from sampled data of Heat Exchanger QAD BDT921
2. To find a continuous time model for Heat Exchanger QAD BDT921 using PMF.
3. To analyse a mathematical model of a heat exchanger.

1.4 Scopes

1. Review and study the Generalized PMF (GPMF), Least Square (LS) and Instrumental Variable (IV) literatures.

2. Develop the software that integrates the data loading, data processing, parameters estimation, model validation and model simulation. The GPMF method will be used to simulate of the parameter obtained based on the transfer function.

3. Estimate the unknown parameters of the system with known model structures using GPMF method based on Instrumental Variable and Least Square.

4. Verify the identified model

5. Examine the obtained model's properties through model simulation

1.5 Expected Results

The expected result of this project is the parameters of continuous time transfer function of the Heat Exchanger QAD Model BDT921. The parameter is obtained based on input-output data of a plant. In this project, analysis will be done using PMF method which determined the parameter of the heat exchanger.

CHAPTER 2

LITERATURE REVIEW

2.1 Plant description and data

Plant description and data of HE-QAD Model BDT921 from the real system have been installed in the Control Laboratory in UTHM. This project covered a study of overall process operation of this plant as a control system plant that uses only air to simulate gas, vapour or steam where air is readily available from a compressor (It is deemed unsafe for students without any industrial experience and safety training to deal with steam or gas).

It provides the gas processes with the measurement and control of their important variables of flow, temperature and pressure. The main purpose of the plant is to heat a liquid in a heat exchanger where the heat is supplied by the hot water which is heated in the boiler. The plant is used to heat up liquid in a heat exchanger where the liquid income from cold water that temperature based on room temperature.

This project is mainly concerned with the modelling of the open loop hot heat exchanger temperature. By comparing the experimental results from the plant with those obtained from the simulation model accuracy of the model evaluated. Preheated tank used in the plant is to warm the cold water from pipe to become hot water from the temperature transfer process.

For the input liquid, its temperature is at room temperature which is around 25°C. The preheated tank maintain the temperature in 60°C. Hot water is heated up in the preheated tank (T12) by a heater at 60° C. In heat transfer process, the energy is stored in one medium as heat capacity is transferred to another medium.

To understand the operation of the control system that controls the boiler drum and heat exchanger, the whole system has been studied. Overview of the real system is as shown in Figure 2.1 and plan for the entire control system is as shown in Figure 3.2. With reference to the overall plan of this system, it is observed that the system of boiler drum control process and heat exchanger consists of a number of key areas of Tank T11, T12 tank, T13 tank and heat exchanger systems. Based on the data used was 1000 for input sample data and the output data temperature.

The hot water in the boiler drum is supplied by T12 tank through pump 12. The flows of hot water is controlled by a valve LCV11. Liquid level transmitter was installed to measure the hot water level in the boiler drum. Readings from the liquid transmitter level is equal to the water level set by the user. If there are any differences between the two readings, the controller level LIC1 1 will take action to open or close the valve so that the flow LCV1 1 and T12 tanks can be controlled and thus the boiler drum water level is controlled.

T12 tank is pre-heating tank because the tank has a heating element that is controlled by the ON / OFF. The function of the water heater at tank T12 is to heat the water in the tank T12. The temperature in the tank T12 is displayed at TIT 12. Temperature allowed here is 60°C and the highest temperature allowed is 65 ° C. This tank has safety ducts that flows the excess water to the drain when the hot water level is at maximum. T12 tank supplies the hot water to boiler drum T11 to make sure it is able of generate hot water boiler in a short time.

T13 tank named as product tank because the tank is filled with the hot liquid. This liquid is a product to be controlled. If the T13 tank level reaches the minimum level, the liquid is supplied through a pipe (PAP). Liquid level in T13 tank is measured by LS13 Limiter switch (limit switch). In general, T13 tank has three levels that can be detected by Limiter Switch LS13 lowest level, medium level and high level.

When the liquid that reaches the liquid level is low, the valve LSV1 1 will open and cause the water pipes to open and allow the fluid in the pipe enters the tank T13. The same situation will occur when the liquid level was in a state of maximum. LSV11 valve closes and water pipes will be closed to prevent fluid from entering the T13 tank. The maximum temperature allowed for the T13 tank is actually 38 ° C, due to the ability of heat-resistant pumps P13 and P14 pump is 40 °. TE13 elements measure the water temperature in the tank and display products TIT13.

Heat Exchanger is a heat transfer that is commonly used to heat and cool a substance in steam process in industry. Primary heating medium commonly used for heat exchanger device is water vapour because it is cheap and easy to get. The steam is also able to bring the capacity of thermal (heat capacity) in large quantities. Most plants that carry the transfer process has an electric boiler designed to produce steam for use in heat exchangers.

Cooling medium that commonly used for this device is also water. When the heating medium flow through the surrounding outer shell tube heat exchangers, the two mediums are not mixed. This means that there are two tubes and channels in the heat exchanger device which in this case the heating medium flows through the channel and the cooling medium will flow through external channels.
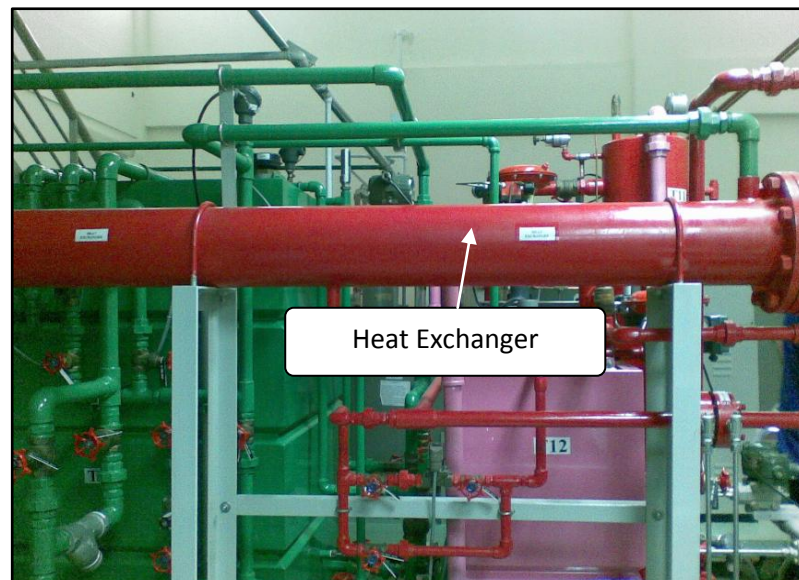
Figure 2.1: Front view of heat exchanger system HE-QAD Model BDT921
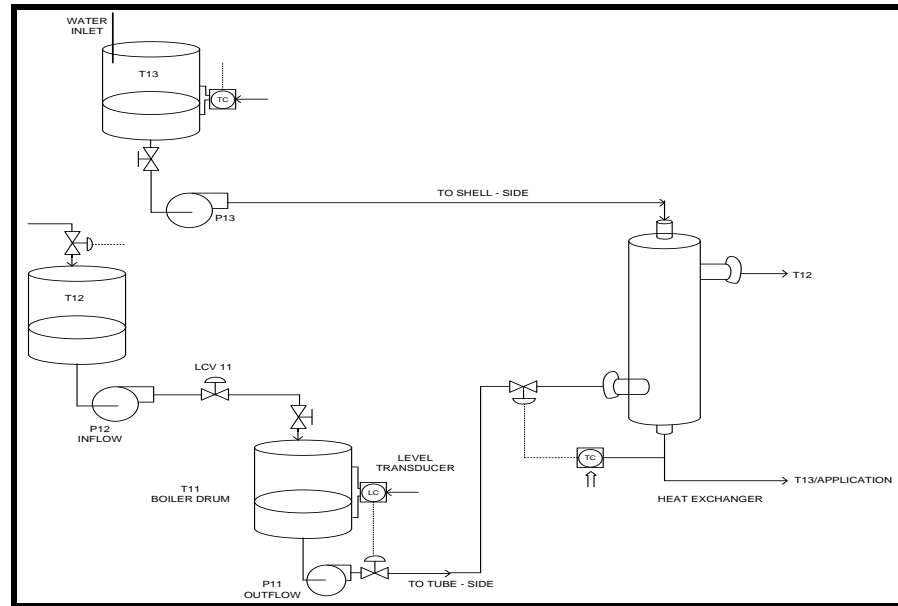
Figure 2.2: Flowing Process of Heat Exchanger QAD BDT 921

Based on the Figure 2.3, in the process of heat exchanger, the temperature controller plays an important role in controlling the temperature in the heat exchanger. Obviously, the temperature controlled variable of the heat exchanger is the temperature of the product liquid because it needs to be heated up at certain temperature required by the operator.

In addition, the temperature of the product liquid outlet is only vary between a small range which is from room temperature as inlet to 50°C therefore the liquid densities and liquid heat capacities us at the constant range which are known. The process of heat transfer will occur when these two liquids flow into heat exchanger.
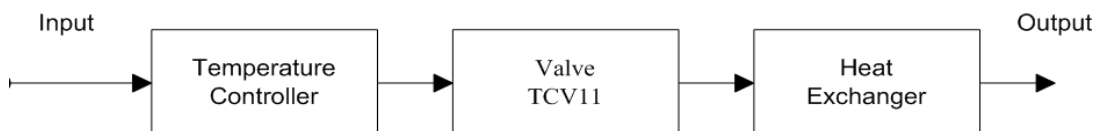
Figure 2.3: Block diagram for temperature control

As the most common heat transfer industrial equipments are the Shell and Tube Heat Exchanger, these equipment are used in HE-QAD Model BDT921 to study the temperature control of a heat transfer process. The open loop since it is

function as the close loop system, the controller must in unity state by setting the TC11 at the controller.

Tables 2.1 show the setting parameter of open loop process to unity the sensor controller. The heater starts from zero and it needs to warm up the heater first. The heating medium from tank T11 is pumped into the tube-side of the heat exchanger and then returned to tank T12. The water (product) required to be heated is pumped into the shell-side of the heat exchanger by pumps P13/P14 from the product around tank 13.

Table 2.1**:** Parameter setting of open loop process of HE-QAD Model BDT 921

Parameter PID	Symbol	Value setting
Proportional	Kp	1 (unity)
Integration	Ti	∞ (maximum)
Derivative	Td	0 (minimum)

Figure 2.4 below shows the PID system for heat exchanger QAD model BDT 921 that allows the study of PID control for control the process of heat transfer using a heat exchanger tube and shell. This process requires heating the product (water) where it is performed until the temperature of the product reaches the preset temperature level (set point, SP). The temperature at the output heat exchanger is measured by the RTD sensor (TE14) and detected by RTD Transmitter (TIT14).

A signal from TIT14 is sent to the PID controller TIC11. Any changes from the set temperature will be corrected by controlling the control valve that controls the rate of entry TCV11 heating medium into the heat exchanger. The control valve also has a current position of the controller in the air (current to water positioner, EP) of TCY11. In the process of heat transfer control, the three terms of the proportion (P), Integral (1) and differentiation (D) are required to achieve good heat transfer control.

Integral (intergral, I) also needed to reduce the offset that occurs from PB. To reduce the heat capacity during the process of heat transfer take place, entry control valve TCV11 are more suitable heating medium to be is installed at the output side of the heat exchanger. This ensures that the heat exchanger tube is always filled with a heating medium even when the control valve is closed.
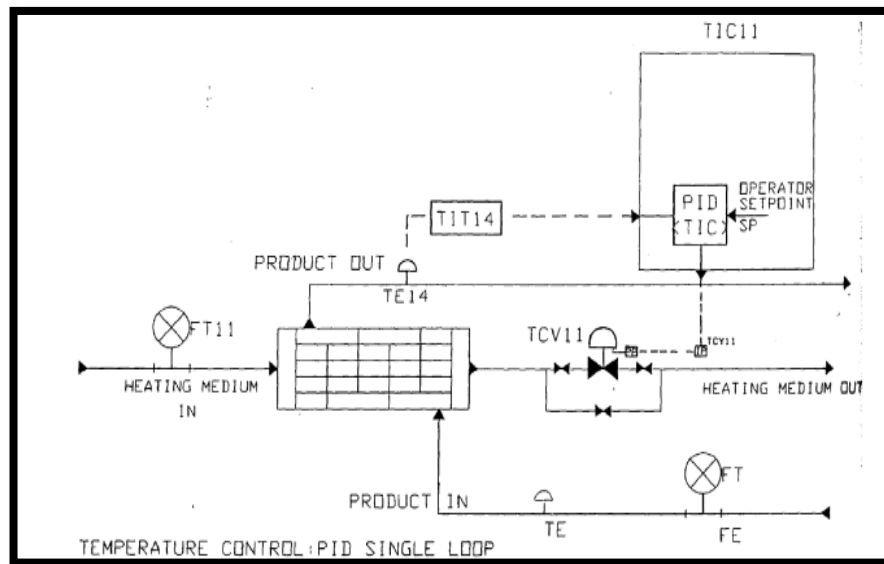
Figure 2.4 : PID system for Heat Exchanger QAD BDT 921

2.2 Previous works

There are a few previous works that have been revised related to this ie. H.Garnier[1,4,6], G.P.Rao[2,9], LennartLjung [3], TatangMulyana [5],RenQingchang [7], Urban Forssell [8], NK Sinha [10], Oliver Hecker [11], Nader Jamali Soufi Amlashi [12], Yuvraj Bhushan Khare Yaduvir Singh [13], Mohd. Fua'ad Rahmat [14], Nguyen-Vu Truong [15], A.V.B Subramahyam [16], Asriel U. Levin [17], Zhenyu Yang [18], L.; De Abreu-Garcia [19], I.D. Landau [20].

H. Garnier [1] studied about a method for estimating continuous-time state-space models for linear time invariant multivariable systems when system outputs are contaminated by noise. The state space model is transformed into an input-output description which is more suitable for parameter estimation. The proposed method does not require the observation of all state variables which is seldom the case in practice. The Poisson moment functional approach is used to handle the time

derivative problem. It is shown that the simple least squares algorithm always gives asymptotically biased estimates in the presence of noise. An instrumental variable algorithm based on Poisson moment functional of system signals is then developed for reducing the bias of the parameter estimates. The least-squares and instrumental variable algorithms are evaluated by means of a numerical example through Monte Carlo simulations.

G.P.Rao [2] presented about Identification of Continuous-Time System. This paper described the system identification problem of continuous time especially for lumped linear and nonlinear models and on those developments that followed earlier surveys by other authors. The continuous time with respect to control engineering application and its model of physical system has been discussed, in particular. The survey on recent developments in identification of non-linear system also has been done. There are also a summary of experiment result for the identification experiment with a simulated model using discrete time and continuous time method. From the result, the discrete time model estimation maybe adequate in some situations but in general if the condition of the identification experiment are not adequately in favour of discrete time method, the results may not be reliable in the sense that the resultant models may be unstable, or even if they are stable they may not be accurate. Furthermore, estimation of continuous time model is free from these problems and It is assures stable and more accurate models, particularly with rapidly sampled data. Then the continuous time and discrete time methods must therefore be integrated, complementing each other to provide a wider set of comprehensive tools with greater choice of options to the system identification community, to assure dependable methods and acceptable results in a wide variety of circumstances.

Lennart Ljung [3] The problem considered is to estimate continuous time (CT) transfer functions from discrete time (DT) input output data {u(tk), y(tk)}. In general, G will be a multiple-input-multiple-output (MIMO) transfer function. It may be noted that multiple outputs pose no problems where each output channel can be treated as a separate problem. Multiple inputs, though, mean conceptual and algorithmic problems: It is a matter of distinguishing the contributions of each input to the output. The input and output signals are CT functions, but sampled at discrete time instants tk. For the problem to be well posed it is formally necessary to know

the inter-sample behaviour of the input signal, so that the continuous time input can be inferred from the sampled values.

H.Garnier [4] presented about a bias-compensation method for continuous time MIMO state-space model identification. The Poisson moment functional approach is used to handle the time-derivative problem. The conventional least-squares algorithm, a recently developed instrumental variable algorithm and the proposed bias-free algorithm are applied to the parameter estimation of a simulated system under different noise levels via Monte Carlo simulations. The bias correction method has been extended for continuous-time MIMO state-space model identification. The state-space model is transformed into an input-output description which is more suitable for parameter estimation. Monte Carlo simulations have demonstrated that the proposed method can yield unbiased parameter estimates in contrast with the simple LS-based PMF algorithm which always gives asymptotically biased estimates. Compared with the IV algorithm, the proposed method gives equivalent results but requires fewer computations. The disadvantages from a practical point of view of the suggested approach may be that the applicability of the BFLS method requires a priori choice of an artificial filter which may in some cases affect the accuracy of the parameter estimates.

Tatang Mulyana [5] studied about a discrete time model of boiler drum and heat exchanger QAD Model BDT 921. The model is obtained from parameter gain values of the real system and then this model will simulate using MATLAB program. The proportional integral differential (PID) controllers are chosen as the control element in discrete form as the real system is using the same control element.This paper proposed an alternative way to obtain the modelling of a boiler drum and heat exchanger.

Hugues Garnier [6] studied about the Matlab Toolbox for data-based modelling of continuous-time dynamic systems. The paper is described about the latest developments for the Matlab CONTSID toolbox. It provides access to most of the time domain continuous time model identification techniques that allow for the direct identification of continuous time models from discrete time data, is in continual development. Planned new release will include more techniques to solve the non-linear continuous-time model identification problems.

Ren Qingchang [7] studied about the dynamic behaviour of a shell and tube counter flow heat exchanger that the heating power of which can be influenced by varying the water flow where it is investigated by experimental identification with Pseudo Random Binary Sequence (PRBS) test signals. Both equation Error model (ARX model) and Output Error Model (OE Model) structures based on the prediction Error Method (PEM) are used in order to do this, and the identification results are compared with each other. Some estimation techniques for this sort of MIMO process are presented and discussed. The proposed identification scheme has proved to function well and to be convenient. The research work represented in this paper is based on a shell and tube counter flow heat exchanger.

Thus, before the controlled behaviour of a heat exchanger can be predicted at the design stage, it is necessary to be able to predict the dynamic behaviour of the heat exchanger. For identification of the dynamic behaviour between the water flow and the outlet temperature, a measuring system was installed at the heat exchanger. The system identification problem is to estimate a model of a system based on observed input output data. There are several ways to describe a system to be estimated. In order to solve their problem, they have to start with single input single output configuration. Since the white noise term e (k) here enters as a direct error in the different equation that is often called as Equation Error Model structure.

For the parameter estimation, having observed the input output data that compute one step ahead prediction errors. Based on this method of estimating parameters can construct models of basically in any structure available. In a nutshell, for describing the dynamic behaviour of the heat exchanger the ARX and OE are adopted, the PEM has been presented (in the least square method). The OE model is obtained by minimizing the one step prediction error, the ARX model is obtained by minimizing the one step prediction error. In this case study, the model which is the PEM method is an analytical one, whereas in the case on an OE model that method is based on the non-analytical of the output and the gradient through a selected predictor model, the parameter estimate with a Gauss Newton procedure.

Urban Forssell [8] studied about prediction error identification of unstable systems using the output error and Box-Jenkins model structures. The predictors in this case generally will be unstable. Typically this is handled by projecting the parameter vector into region of stability which underlying system in unstable. In case

the parameters are estimated using some numerical search that requires gradients of the predictor to be computed. Suppose now that to use an output error or a Box Jenkins, model structure. Then the predictors will generally be unstable which seemingly makes these model structures useless in these cases. The noise properties are less interesting so that it would be natural to use output error model structure. Since unstable plants cannot be handled using output error models the finally has been that this approach cannot be used when the plant is unstable.

A problem when identifying systems in closed loop directly is that the results will be biased unless the noise model accurately describes the true noise characteristics. This has traditionally becomes a main issue in the system identification literature that for alternative in identification methods. The standard output error model structure should be modified to cope also with unstable systems. In a nutshell, this paper proposed new version of the well-known output error and Box-Jenkins model structure that can be used for identification of unstable system. The new model structures are equivalent to the standard ones, as far as number of parameters and asymptotical results are concerned, but guarantee stability of the predictors.

G.P.Rao [9] examines the direct approaches included in the non-commercial Matlab CONTSID toolbox and indirect approaches available in the commercial Matlab System Identification (SID) toolbox in the light of the results of an extensive simulation experiment in which each approach is subjected to a set of Monte Carlo simulations. The methods are assessed with reference to their performance in terms of accuracy and most importantly dependability. The latter criterion refers to 'stability rate' which means the number of runs that yield a stable model. The results of this study clearly show that the indirect route to CT model identification is not fully dependable. Although DT model based methods have proved to be highly successful and useful for many purposes, it is desirable not to use them as an intermediate step on the path towards CT models. This suggests that system identification tools deserve to be enhanced in their capacity; they should offer wider choice of both models and methods. It is appropriate to have a system of tools unifying the various approaches so that it becomes dependable in a situation characterized by a diversity of needs. The SID and CONTSID toolboxes are complementary. With an appropriate unification arrangement, they can form a unique

system of tools for system identification that will be comprehensive, more dependable and effective.

N.K Sinha [10] this paper presents an introductory survey of the methods that have been developed for identification of continuous-time systems from samples of input-output data. The two basic approaches may be described as the indirect method, where at first, a discrete-time model is estimated from the sampled data and then an equivalent continuous-time model is calculated, and the direct method based on concepts of approximate numerical integration, where a continuous-time model is obtained directly without going through the intermediate step of first determining a discrete-time model.

Oliver Hecker, Oliver Nelles, Olaf Moseler [11] This paper deals with identification and control of a highly non-linear real world application. The performance and applicability of the proposed methods are demonstrated for an industrial heat exchanger. The main difficulties for identification and control of this plant arise from the strongly non-linear centre and the widely varying dead times introduced by different water flows. The identification of this three input one output process is based on the local linear model trees (LOLIMOT) algorithm. It combines efficient local linear least-squares techniques for parameter estimation of the local linear models with a tree construction algorithm that determines the structure of their validity functions. Furthermore, a subset selection technique based on the orthogonal least-squares (OLS) algorithm is applied for an automatic determination of the model orders and dead times. This strategy allows designing a wide range high accuracy non-linear dynamic model of the heat exchanger on which the predictive control approach is based on. The non-linear predictive control takes the speed and limit constraints of the actuator into account and leads to a high performance control over all ranges of operation. A non-linear predictive control scheme based on a local linear fuzzy model combined with an on-line optimization procedure is proposed, The real world process under investigation is an industrial steam heated heat exchanger with a strongly nonlinear dynamic behaviour and operating point dependent dead times. A wide range high accuracy model was identified leading to a high performance predictive control that is able to operate at the actuator constraints. A problem that needed to be investigated in deathly in further in the future is the automatically tuning of the prediction horizon and disturbance filter time constant.

Nader Jamali Soufi Amlashi, Amin Shahsavari, Alireza Vahidifar, Mehrzad Nasirian [12] This paper addresses the non-linear identification of liquid saturated steam heat exchanger (LSSHE) using artificial neural network model. Heat exchanger is a highly non-linear and non-minimum phase process and often its working conditions are variable. Experimental data obtained from fluid outlet temperature measurement in laboratory environment is being used as the output variable and the rate of change of fluid flow into the system as input is also being used. The results of identification using neural network and conventional non-linear models are compared together. The simulation results show that neural network model is more accurate and faster in comparison with conventional non-linear models for a time series data because of the independence of the model assignment. In this paper, the artificial neural network model was used to predict the heat exchanger considering to temperature of the outlet water as output system and rate of changes in inlet water as input. In comparison with conventional non-linear models like NARX, this method do not need to model assignment and with considering to performance like MSE and SSE and the cost function has a quick and accurate prediction. Consequently, the artificial neural networks model can be used as efficient tool in identifying heat exchanger for design objectives and design controller.

Yuvraj Bhushan Khare Yaduvir Singh [13] Heat exchanger system is widely used in chemical plants because it can sustain wide range of temperature and pressure. The main purpose of a heat exchanger system is to transfer heat from a hot fluid to a cooler fluid, so temperature control of outlet fluid is of prime importance. To control the temperature of outlet fluid of the heat exchanger system a conventional PID controller can be used. Due to inherent disadvantages of conventional control techniques, model based control technique is employed and an internal model based PID controller is developed to control the temperature of outlet fluid of the heat exchanger system. The designed controller regulates the temperature of the outgoing fluid to a desired set point in the shortest possible time irrespective of load and process disturbances, equipment saturation and nonlinearity. The developed internal model based PID controller has demonstrated 84% improvement in the overshoot and 44.6% improvement in settling time as compared to the classical controller. This paper takes a case study of heat exchanger system and evaluates

different methods to control the outlet fluid temperature. Four different kinds of controllers are designed to control the outlet temperature of fluid and the performances of these controllers are evaluated by two different methods. One of the methods for performance evaluation is the time domain analysis of overshoot and settling time and other method is calculation of performance Indices. Firstly a classical PID controller is designed to achieve the control objective. But due to the unsatisfactory performance of the PID controller a feed forward controller is designed and placed in the forward path of the system. To further increase the efficiency of the system the internal model based PID controller is designed and implemented. The internal model based PID controller gives satisfactory performance in both steady state and transient state in time domain analysis. The performance indices of all the controllers are also evaluated. This paper takes the process model to be the same as the process, which is practically impossible to achieve.

Mohd. Fua'ad Rahmat, Rosli Omar, Hishamuddin Jamaluddin [14], This paper introduces a Graphical User Interface (GUI) application in system identification and parameter estimation of dynamic systems using Generalized Poisson Moment Functionals (GPMF) method based on Instrumental Variable (IV) algorithm. The GUI based on MATLAB consists of data preprocessing, parameter estimation, model validation and model simulation. A step by-step instruction on how to use the GUI employed in the study is also presented. A validation process had been implemented using cross validation process. Simulation process based on the estimated mathematical model was performed to analyze the dynamic behaviors of the model. From the simulation results and analysis, it could be concluded that the model obtained using this GUI is reliable. It has been presented that the GUI that used the GPMF method based IV algorithm have successfully identify the appropriate model from input and output data of a system. Of the existing continuous-time parameter estimation approaches based on an equation error approach which use transfer function models, the Poisson Moment Functionals approach is claimed to be one of the best under noisy conditions. IV estimator was considered rather than the least square because it gives more accurate estimation and reduced the bias of the parameter estimated.

Nguyen-Vu Truong [15], In this paper, nonlinear identification of a Liquid-saturated Steam Heat Exchanger using Wavelet based State Dependent Parameter (WSDP) models is presented. This is a highly non-linear, non-minimum phase process, and often operated under varying conditions. Here, in order to characterize such dynamics, 2-D WSDP model is used. The simulation results demonstrate the merit of the identified model. This paper has presented an efficient non-linear system identification of a Liquid-saturated Steam Heat Exchanger Wavelet based State Dependent Parameter models, 2-DWSDP in particular. Via SDP model structure, it provides valuable insight into the system's dynamics, visualizing where the non-linearities reside, and function within the system. The identification results have demonstrated that this process is compactly represented by the identified mathematical model, and its associated multi-variable dependent nonlinear dynamics have been effectively captured. This, in turn, proves the merit and advantages of such a non-linear system identification approach.

A.V.B Subramahyam, G.P Rao [16] , The paper presents a new approach towards unbiased estimation of the transfer functions of continuous-time SISO systems via Markov parameters. A new set of parameters known as Markov-Poisson parameters is introduced to generalise the definition of Markov parameters, thereby lending much flexibility to the estimated model. An effective algorithm giving continuous-time transfer functions through the estimation of such models, and its recursive version are discussed in detail. Numerical examples are included to illustrate the proposed method and its superiority over some existing ones. The problem of identifying linear CT SISO systems in their TF format using Markov parameter models at intermediate stages has been considered. The proposed approach could replace the IV methods of LS estimation to give bias free estimates, as justified by the results of the preceding Section. As a whole, this work may be viewed as the first step in the use of Markov parameter models as an alternative for TF models for CT system identification. A more intensive and exhaustive follow up must be made to remove all the obstacles on the way to reaching practical applications.

Asriel U. Levin and Kumpati S. Narendra [17], A general approach to the design of neural network based controllers for non-linear dynamical systems is discussed in the paper. The state vector of the no-nlinear plant to be accessible and the main objective is to stabilize the plant around an equilibrium state. The

theoretical and practical question that arises are examined and the prior information needed to design the controllers are specified. The most important aspect of the methods proposed is they are practically viable. It is demonstrated trough simulation studies on the stabilization of non-linear system for which other method are not currently available. The problem of control becomes substantially more complex when the state of the system is not accessible and control has to be achieved using input-output data.

2.2.1 Summary of Previous Works

Table 2.2: The summary Of Previous Works

Author	Problem	Method	Tools	Result
H.Garnier [1] (2007)	To determine mathematical model	PMF	LS based PMF algorithm and Monte Carlo simulation analysis	A mathematical model is obtain
G.P.Rao [2] (March 2006)	Compared between DT and CT models	CT and DT method	CONTSID toolbox, SID toolbox	Determine which models more stable and accurate.
LennartLjung [3] (1987)	Estimate CT transfer function from DT input output data	SVF, GPMF and Refined	CONTSID, CAPTAIN and SITB	Transfer function is obtained and been compared
H.Garnier [4] (December 1997)	Compared between bias-compensation and IV algorithm method	bias-compensation, IV algorithm	Monte Carlo Simulations	Compared between methods
TatangMulyana [5] (2011)	To determine mathematical model	Hammerstein-Wiener	M-File Matlab	A mathematical model is obtain

H.Garnier [6] (2002)	Introduce application of CONTSID toolbox	ARX, OE, Box Jenkins	CONTSID toolbox	Outlined main features of CONTSID toolbox
RenQingchang [7] (1990)	To determine mathematical model	ARX and OE model	MATLAB SIMULINK and Identification.	A model is obtained
Urban Forssell[8] (1998)	To determine mathematical model	BJ model and OE model	MATLAB SIMULINK and Toolbox	New version of OE and BJ model structures
G.P.Rao [9] (1982)	CT algorithm	PMF	MATLAB	Algorithm for CT is obtained
N.K Sinha [10] (April 2000)	Compare of DT and CT	Direct and Indirect	SID and CONTSID toolbox	Advantage and disadvantage of direct and indirect methods
Oliver [11] (June 1997)	deals with identification and control of a highly non-linear real world application	Local linear Fuzzy	Local linear model trees	A non-linear predictive control scheme based on a local linear fuzzy model combined with an on-line optimization procedure is proposed
Nader Jamali [12] (February 2013)	Compare result identification between using neural network and conventional nonlinear models	NARX	Artificial neural network	ANN model can be used as efficient tool in identifying heat exchanger for design objectives and design controller
Yuvraj Bhushan [13] (October 2010)	Design PID controller	-Time domain analysis -Calculation of perfomances	MATLAB	Internal model based PID controller is designed.

Mohd Fu'ad Rahmat [14] (Jun 2002)	Design GUI application for system identification	PMF	GUI	Introduce GUI application for system identification
Nguyen Vu Truong [15] (October 2011)	To determine mathematical model	WSDP	MATLAB	Mathematical model is obtained
Subramah yam [16] (January 1993)	Estimate parameters for transfer function	Markov Poisson	MATLAB	Parameter of transfer function is obtained
Asriel U. Levin [17] (March 1993)	Design neural network based controller	Neural network	ANN MATLAB	Simulation studies on stabilization of non linear system

CHAPTER 3

METHODOLOGY

3.1 Continuous-time System Identification Algorithm

Direct approaches for continuous-time model identification may be seen to consist of two stages [22]:

(1) **The primary stage** in which the system of parameter estimation equation is derived from the dynamical model of the system to be identified (GPMF).

(2) **The secondary stage** in which the continuous-time parameters are estimated within the framework of a parameter estimation method Instrumental Variable (IV).

The primary stage arises out of the derivative measurement problem. The GPMF transformation that was derived in this first stage converts the process differential equation into algebraic form. This method is helpful in reducing the calculus of continuous-time dynamical systems into appropriate algebra required for parameter estimation.

The secondary stage in this study was independent of the original model form and depends only on the system of Instrumental Variable and Least Square algorithm arising out of it. These two stages are shown in Figure 3.1.
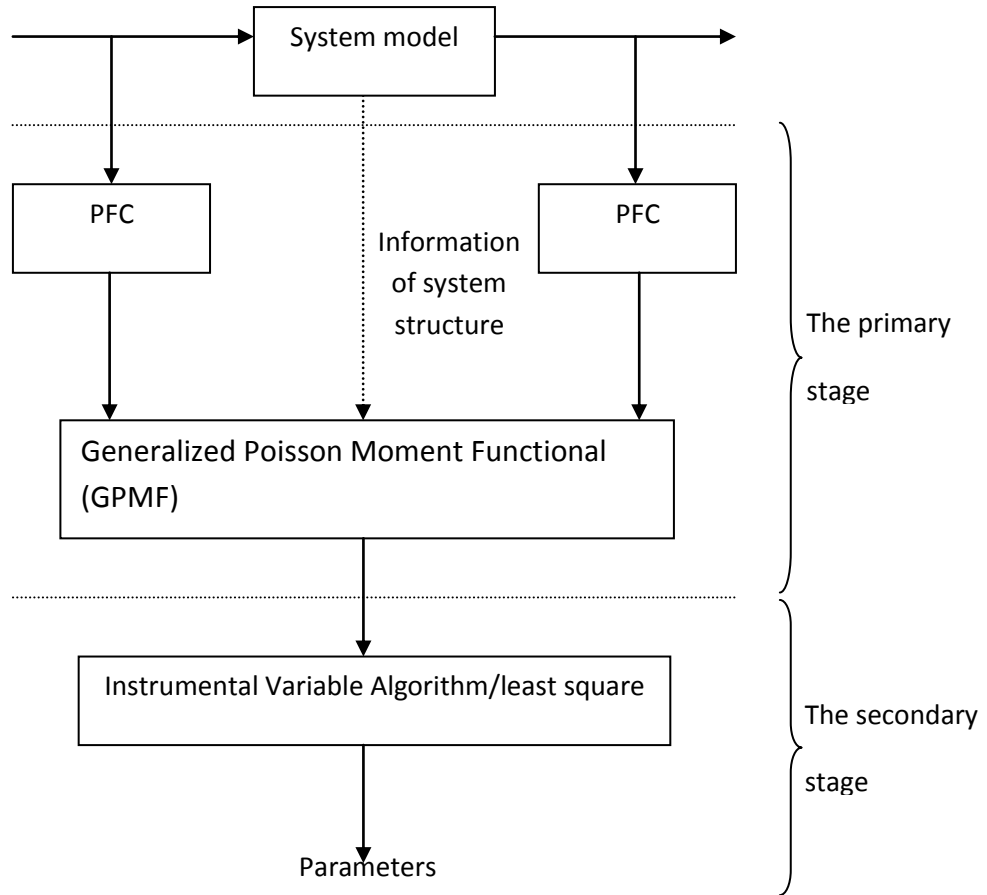
Figure 3.1: Parameter estimation in continuous-time models

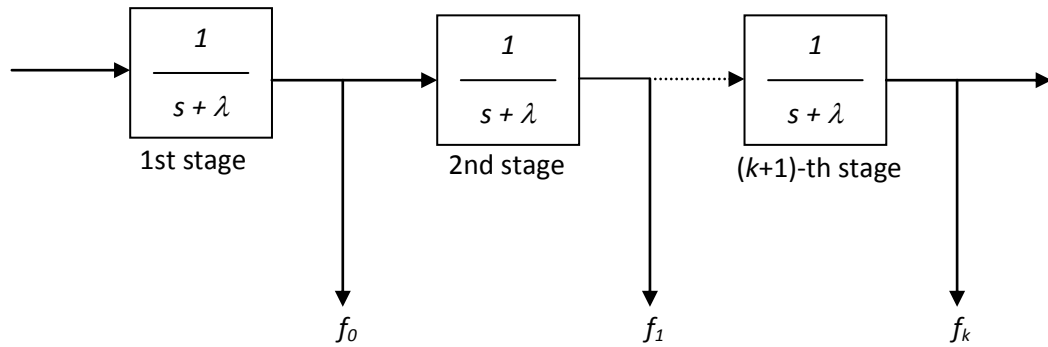PFC denotes the Poisson Filter Chain operation. The PFC is shown in Figure 3.2.

Figure 3.2: Poisson filter chain (PFC)

Each element of the PFC has a transfer function of the form $\dfrac{1}{s+\lambda}$. λ is a positive real number. The number of stage of PFC depends on the structure of the model. The PFC operation is such that it, while retaining the parameters of the continuous model in their actual original form, facilitates generation of the appropriate measurements for the parameter estimation equation. The PMF of the signals are generated by passing them through PFC. In GPMF, the generalized PFC (GPFC) was used. Hence each element of the GPFC has a transfer function $\dfrac{\beta}{s+\lambda}$ where β is a positive real number.

3.1.1 Poisson Moment Functionals (PMF)

A signal $f(t)$, $t \in (0, t_0)$, is treated as a distribution or generalized function, and expanded about a time instant t_0 in equation (3.1) exponentially weighted series

$$f(t) = \sum_{k=0}^{\infty} M_k\{f(t)\}\exp[-\lambda(t-t_0)]\delta^{(k)}(t-t_0) \qquad (3.1)$$

where $\delta^{(k)}(t - t_0)$ is the k-th generalized time derivative of an impulse distribution occurring at $t = t_0$

$$M_k\{f(t)\} \equiv f_k^0 = \int_0^{t_0} f(t)\,p_k(t_0 - t)\,dt \qquad (3.2)$$

with

$$p_k(t_0) \equiv p_k^0 = \frac{t_0^k}{k!}\exp(-\lambda t_0) \qquad (3.3)$$

and λ is a positive real number. p_k^0 is called the k-th order Poisson pulse function at t_0 and f_k^0 is termed as the k-th PMF of $f(t)$ about $t = t_0$. f_k^0 may be viewed as the output due to an input $f(t)$, at $t = t_0$, of the $(k+1)$–th stage of a cascaded filter with identical stages, also called the PFC, each element of which has a transfer function $1/(s + \lambda)$ as indicated Figure 3.2.

The PMF transformation about $t = t_0$ of $y(t)$ viz. $M_k\{y(t)\}$ as in equation (3.4)

$$M_k\left\{\frac{dy(t)}{dt}\right\} \equiv \int_0^{t_0} \frac{(t_0-t)^{k-1}}{k!} e^{-\lambda(t_0-t)} \frac{dy(t)}{dt} dt \tag{3.4}$$

integrating by parts, the right hand side of the above equation yields equation (3.5)

$$\frac{(t_0-t)^k}{k!} e^{-\lambda(t_0-t)} y(t)\Big|_0^{t_0} - \int_0^{t_0}\left[\frac{(t_0-t)^{k-1}}{(k-1)!} e^{-\lambda(t_0-t)} + \lambda\frac{(t_0-t)^k}{k!} e^{-\lambda(t_0-t)}\right] y(t) \, dt, \tag{3.5}$$

implying that resulted equation

$$M_k\left\{\frac{dy(t)}{dt}\right\}_{t_0} \equiv M_k\left\{y^{(j=1)}(t)\right\}_{t_0} = y_{k-1}^0 - \lambda y_k^0 - p_k^0 y^{(0)}(0), \tag{3.6}$$

wherein the subscript '0' signifies the transformation about $t=t_0$, the subscript k denotes the order of the PMF and the subscript (j) denotes the order of the derivative term; $y^{(0)}(0)=y(t=0)$. p_k^0 is the value of the Poisson pulse function of order k at $t=0$. By analysis similar to the above, it can be shown as equation (3.7)

$$M_k\left\{y^{(2)}(t)\right\}_{t_0} = y_{k-2}^0 - 2\lambda_{k-1}^0 + \lambda^2 y_k^0 - (p_{k-1}^0 - \lambda p_k^0)y^{(0)}(0) - p_k^0 y^{(1)}(0) \tag{3.7}$$

Notice how the PMF's of derivatives are expressed as linear combinations of those of the original function itself. Also recall that these can be measured as the outputs of a Poisson filter chain excited by the original function.

Let's consider a differential equation as (3.8)

$$a\frac{dy(t)}{dt} + y(t) = bu(t) \tag{3.8}$$

If we take the k-th PMF transformation of Equation (3.8) about t_0 we get equation (3.9)

$$aM_k\left\{\frac{dy(t)}{dt}\right\}_{t_0} + M_k\left\{y(t)\right\}_{t_0} = bM_k\left\{u(t)\right\}_{t_0} \tag{3.9}$$

Inserting Equation (3.6) in the Equation (3.9), yields equation (3.10a)

$$a\left[y_{k-1}^0 - \lambda y_k^0 - p_k^0 y^{(0)}(0)\right] + \left[y_k^0\right] = b\left[u_k^0\right] \tag{3.10a}$$

or

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